An Expert System With External Optimization Module for Quality Control Decisions

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ABSTRACT

Although statistical quality control is already largely automated for the gathering and processing of data, improperly implemented quality control can yield erroneous results, which may go unnoticed indefinitely in a manufacturing environment. Quality control, which combines decisions and interpretations based on analytical data, on heuristics, and on user judgment, is suited for rule based expert systems. Many commercial software packages store data and perform calculations for quality control; this comprehensive expert system, named Quincy, is envisioned as a complement to those.

Consisting of 118 rules, 246 facts, 16 optional explanations, 34 textual expansions, 36 displays and an optional optimization module, Quincy focuses on three main areas of quality control decision making:

A. Selection of applicable control charts for various manufacturing processes.

B. Interpretation and generic diagnoses of control chart results.

C. Selection of appropriate acceptance sampling plans.

Quincy is designed to be applicable to a wide number of manufacturing organizations, even those with limited computing experience or availability. The expert system shell has a user friendly interface, an undemanding PC hardware platform, and is quite portable. The C optimization module operates transparently to the user, and is also portable. Furthermore, Quincy is built modularly so that future additions and modifications can be made relatively simply.

1.0 INTRODUCTION

Artificial intelligence includes several fields of scientific research including natural language processing, artificial neural networks and expert systems. All are concerned with replicating and sometimes improving upon human abilities. For expert systems, the human traits of knowledge storage, rule of thumb invocation and inferential reasoning are the areas of interest, and interpretation, prediction, design and monitoring are the tasks addressed [1].

Manufacturing quality control is a large field aimed at optimizing quality by preventative and corrective measures; variables in product design, materials, processing, ambient conditions and fabrication are brought under control [2]. It seeks to balance high quality and the costs of maintaining such quality. Using statistical methods to achieve quality control, statistical quality control was popularized by W. A. Shewhart and his group at Bell Laboratories in the first half of this century and has been expanded by such notables as W. E. Deming and J. M. Juran until nearly all businesses currently use some form of it.

Engineering a knowledge base for statistical quality control is viable since it is a well structured domain with both analytical and heuristic solutions. A human expert can make very good decisions in little time, whereas a non-expert may need significant training and exposure to reach the same decision making capability. Statistical quality control fulfills three fundamental criteria for an expert system candidate - relevancy, feasibility and optimality [3]. Commercial software, such as spreadsheets and statistical packages, can store data and perform the calculations of quality control; this expert system, named Quincy, is designed as a complement to those to assist with decision making and complex analysis.

This chapter will briefly review control charts and acceptance sampling plans, and cite previous expert system applications to quality control. Then, the system structure including reasoning will be presented. Finally, each of the three main areas of Quincy are discussed in more detail, and conclusions reached.

2.0 OVERVIEW OF CONTROL CHARTS AND ACCEPTANCE SAMPLING PLANS

Control charts are commonly used in manufacturing environments to analyze process parameters to determine if a controlled process is within or out of control. Some processes which benefit from control chart tracking are filtration, extraction, fermentation, distillation, refining, reaction, pressing, metal cutting, heat treatment, welding, casting, forging, extrusion, injection molding, spraying and soldering [4]. Control charts are plots of sequential points of critical parameters of sample lots. Sample size and sampling interval are generally fixed. Control charts measure location (such as mean or proportion) and variability (such as range or standard deviation). Although computationally simple, control charts are sometimes complex to correctly use because the sample points come from probabilistic distributions and usually require interpretation by a skilled user.

W. A. Shewhart first proposed the use of control charts in 1931, which commonly bear his name as Shewhart control charts [5]. Figure 1 shows a portion of a typical control chart with 3σ limits Through the ensuing years many different formulations became known, such as moving average and range charts, proportion (P) charts, number of defectives (C) charts, cumulative sum (cumsum) charts, and control charts with warning limits [6, 7, 8]. However, most manufacturers use versions of the early control charts which track sample mean (X-bar charts) and sample range (R charts) as checks on the process state and the process variability [7]. These charts are best suited for processes which typically experience large shifts when out of control, or the penalty for out of control production is not extreme [8]. One reason these X-bar and R charts may be so popular among all processes is that to select a more appropriate control chart requires greater expertise than is sometimes available.

Figure 1 About Here

A difficulty with control charts is the determination of whether a process is actually within control or not. Since sample points are subject to noise due to measurement, human and other factors, they form a non-specified probabilistic distribution. An extreme point may come from a process which is, in fact, under control (a Type I or α error). Or a point within boundaries may come from a process which has shifted to out of control (a Type II or β error). A Type I error costs time and money when the process is investigated to find the cause of the out of control situation (the assignable cause) when, in fact, there is none because the process is not out of control. A Type II error allows a process to continue even though it is out of control. Besides control limits, there are certain patterns of sample points which indicate the process in moving towards, or cycling through, undesirable situations. Again, classifying these points correctly is stochastic, and requires a certain expertise in the process and the concept of control.

Another important decision area in quality control is the selection of acceptance sampling plans. Acceptance sampling can be done by the supplier or buyer. It aims to ensure a certain level of quality while minimizing sampling costs. Choosing an acceptance sampling plan depends on the nature of the product, sampling costs, the relative importance of rejecting good items or accepting bad items, the overall quality level of items, and the sample size and variability. Once a plan has been selected, certain key variables can be calculated to estimate the average quality level, and the cost and effort of sampling.

Some earlier work has been done to relate expert systems to control charts. Most of these have selected proper control methodologies and advised on the analysis of the selected methodologies [9, 10, 11, 12, 13, 14]. Quincy, an earlier version of which was introduced in [15], is different from this previous work in two respects. First, it is more comprehensive than earlier expert systems since it includes acceptance sampling and control chart diagnoses along with control chart selection. Second, it integrates with an external optimization module transparently so that the user can obtain optimal sampling parameter values, along with the expert system recommendations, within one consultation.

3.0 THE EXPERT SYSTEM STRUCTURE

One of the reasons for the popularity of knowledge based systems is the proliferation of sophisticated but developer and user friendly expert system shells. These shells differ from conventional programming by relying on heuristics rather than algorithms, being symbolic instead of numerically oriented, and by processing interactively, not sequentially [16]. This application was built on version 1.2 of Level5, an expert system shell, from Information Builders, Inc. running on a PC under DOS. Level5 for DOS works by compiling an ASCII text file with the suffix, PRL, into an executable knowledge base with suffix, KNB. The ASCII file can be created in any text editor or word processor as long as the format required by the Level5 compiler is followed. Level5 can work with external programs, and the expert system described in this chapter uses a C optimization module.

3.1 SYSTEM FEATURES AND STRUCTURE

Quincy is rule based, i.e. the primary intelligence lies in its rules. Each rule is *modus ponens* (IF/THEN) and consists of antecedent conditions, known facts and additional user supplied answers resulting in one or more consequents (conclusions and actions). The inference engine (logic system) pursues the selected goal by backward chaining. Backward chaining is efficient when the problem has a well defined goal and means of selection to reach that goal. Quincy employs exhaustive reasoning, which means the inference engine does not stop when one applicable conclusion is reached. Reasoning continues until all possible avenues are explored. Exhaustive reasoning allows more than one conclusion to a given antecedent to be reached, and this, in turn, is used to weigh the value of the different conclusions.

This system has 118 rules, 246 facts, 16 optional explanations, 34 text expansions and 36 displays. Figure 2 shows the present and proposed system structure of Quincy. Facts are either attribute (qualitative variables), numeric (numeric variables) or string (literate variables). Quincy employs goal selection, i.e. allows the user to choose one of the three main areas (control chart selection, control interpretation or sampling plan selection) for consultation. For any question, a user may respond with "Unknown" and the system will attempt to proceed with the analysis without that information. Quincy has been designed to minimize user supplied information and is therefore very limited in its ability to reason with unknown responses. At the end of the session, the user may optionally ask for the chain of reasoning utilized, the answers to all questions and the conclusions to all rules. These facilities are contained within the Level5 software shell.

Figure 2 About Here

Further enhancing Quincy's usability are explanations, text expansions and displays. Explanations offer optional clarification on questions to the user or elaborate on term definition. They are interactively selected using Function Keys by the user during the consultation. Text expansions are used for terms which are briefly expressed in the rules. The expansion is automatically shown to the user instead of the brief rule expression during the consultation. Displays are automatically shown too, and are usually used to show the user the conclusions and recommendations of the system. Some Quincy displays also show confidence factors as bar graphs and the calculated values to numeric variables.

Several other concepts have been applied. To handle uncertainty confidence factors for various system generated conclusions are employed. Confidence, or certainty, factors are typically stated in percentages from zero to one hundred, and allow the system to exhaustively pursue reasoning avenues which may not be wholly true and to suggest solutions with varying confidence. In this system, user responses are minimal and are largely based on factual conditions, so use of certainty factors is confined to only a few items, namely the control chart selected and the sampling plan selected. These can have multiple attributes, e.g. there can be more than one suggested sampling plan or control chart. Should there be more than one applicable control chart or acceptance sampling plan, Quincy outputs all applicable choices and their confidence factors to the user.

Some basic calculations for acceptance sampling are done within the expert system, as are some error checks. If the user violates the allowable entries, the system outputs an error message and "loops." Looping lets the user input the information again, correcting previous errors, without terminating the consultation.

Finally, since expert systems are not designed to act efficiently for storage and manipulation, this shell allows exporting and importing of data to other programs. Quincy interfaces with a C program performing an advanced optimization algorithm, although the data transfer is completely transparent to the user. The C program is QUINCY.EXE. To interface with the expert system shell, QUINCY.EXE uses a C header file, ASCIIPRM.H. Results are returned and displayed to the user by Quincy.

3.2 DISKETTE FILE DESCRIPTIONS

The diskette included with this book contains a directory, QUINCY, which includes the compiled knowledge base, **QUINCY.KNB**, and the compiled C optimization module, **QUINCY.EXE**. To run the knowledge base, Level5 for DOS must be installed on the PC, and QUINCY.KNB and QUINCY.EXE must be placed in a directory called "PRL". The QUINCY directory on the diskette also contains three ASCII files:

1. **QUINCY.PRL**. This is the ASCII version of the expert system. QUINCY.PRL can be inspected by the reader with ease. Annotations are indicated with a "!" at the start of the line. Words in all capitals signify Level5 commands or keywords. The file begins the title screen, then defines all the variables as either attribute, numeric or string. These variables are used to match antecedents and consequents during rule firing After a few system parameters are set, an outline of the major portions of the knowledge base appears as "Goals of the system." Rules follow, with each rule labeled by a lettered phrase to designate its logical grouping, and by a sequential number to designate the individual rule. After the rules, the automatic text displays (TEXT), the screen displays to the user (DISPLAY), and finally the optional text expansions (EXPAND) are listed. In the displays, the command BAR produces a bar graph of confidence factors.
2. **QUINCY.C**. This is the ASCII file of the C program for optimization of sampling method when the control selected is X-Bar and R. Nine numeric variables are passed from the expert system during the consultation to the C optimization program as variables inval[0] through inval[8]. Four numeric variables found by iterative search are returned from the C program to the expert system for display to the user. These are labeled in the C program as size, bestfn, bestk and besth (optimal sample size, optimal cost of control, k value for upper and lower control chart limits and optimal sampling interval).

3. **ASCIIPRM.H**. This is the ASCII file of the C header file needed by QUINCY.C. It controls the passing of data back and forth from the expert system and the C program.

4.0 THE SYSTEM DOMAIN

The knowledge based system does not attempt to include those areas better handled by traditional systems, such as data storage, statistical analysis and graphical displays. It does focus on three main areas of decision making:

a. Selection of applicable control charts for various processes.

b. Interpretation of control chart results.

c. Selection of appropriate acceptance sampling plans, with applicable calculations.

Together, these three areas form major decision points of statistical quality control. What is the form of control (control charts for process monitoring and acceptance sampling for components or finished goods), and what is that control expressing? The success of human decisions depend on the expertise of the quality control engineer and time allowed for decision making.

4.1 SELECTING CONTROL CHARTS

Control charts have been used effectively as graphic means to measure the state of a process. The process is tracked over time by mean, variability or range, and is considered out of control when specific limits are reached, such as 3σ. To select a proper control chart, the user must know the objectives of control, the conditions of obtaining control measurements and the applications of the different control charts. The portion of the knowledge based system which selects control charts contains 43 rules to select one of eleven charts. It also optionally sends data to an external C optimization routine to calculate the optimal sample size, sampling interval, k limits for upper and lower control chart bounds, and the cost of control.

The portion of the knowledge based system which selects control charts could be easily modified to accommodate fewer control chart alternatives, depending on those traditionally used by the particular manufacturer. An initial decision is whether monitoring will be of attributes or variables; attribute data is whether an item should be accepted or rejected whereas variable data is measured on a continuous scale. Attribute data is monitored if time, cost or technological methods preclude measurement [17]. An example of attribute monitoring is a go or no go test, such as if a scratch exists or whether a color is proper. Measurable product characteristics are weight, dimensions, specific gravity, tensile strength, impurity, resistance and voltage. In some cases, variable data will lend itself to one sided limits only, e.g. strength having only a lower limit and impurity only an upper limit [17]. If items to be measured are from a homogeneous sample, e.g. pH of a chemical solution, more than one measurement per sample is redundant, and an individuals chart is recommended.

For users of X-bar and σ charts and X-bar and R charts with computer capability a further probe is done to determine if cumulative sum (cumsum) charts would be appropriate. These charts are not true Shewhart control charts but are easily understood plots designed for use on the production line. They detect small process changes more quickly and require smaller sample sizes. Also for X-bar and R charts the user has an option of running an optimization module to determine proper sample size, the minimum cost of control, the k value to determine upper and lower control limits and the optimal sampling interval [18]. These parameters further assist the user to precisely design a superior control chart. The optimization routine is a C program, external to the knowledge base, based upon a single assignable cause model approximated by A. J. Duncan [19], W. K. Chiu and G. B. Wetherill [20], and D. C. Montgomery [21]:

$$E(L) = \frac{a_1 + a_2 n}{h} + \frac{a_4\,[h/(1-\beta) - \tau + gn + D]}{1/\lambda + h/(1-\beta) - \tau + gn + D} + \frac{a_3 + a'_3 \alpha \exp^{-\lambda h}/(1 - \exp^{-\lambda h})}{1/\lambda + h/(1-\beta) - \tau + gn + D}$$

Where:

E(L)	expected cost per hour *
α	probability of false alarm, $\alpha = 2 \int_k^{\infty} \phi\,(z)\,dz$
$\phi\,(z)\,dz$	standard normal density
k	constant for setting upper and lower control chart bounds *
h	time interval for sampling *
τ	expected time of occurrence of single assignable cause between consecutive samples

$1/\lambda$	expected length of out of control period (based on Poisson distribution) #
β	probability of type II error
$h/(1-\beta) - \tau$	expected length of out of control period
δ	magnitude of single assignable cause #
n	sample size *
g	time required to take sample #
D	time required to find the assignable cause #
$a_1 + a_2n$	cost of taking the sample #
a_3	cost of finding an assignable cause #
a'_3	cost of investigating a false alarm #
a_4	hourly penalty cost associated with production in the out of control state #

* Is found by optimization routine.
# Entered by user.

4.2 INTERPRETING CONTROL CHART RESULTS

Often control chart results are not obvious and need skillful opinion to determine whether a process is out of control. The sub module of the system addressing this aspect has 29 rules divided into two main domains - first, interpreting the general shape of points, and second, determining control condition from the number and position of data points. The system distills well known rules of thumb for interpretation of control chart results [22, 23], leading the user through applicable questions to arrive at a probable diagnosis.

The shape of sequential control chart points can often indicate vital information about the process. Quincy looks at five common variations - trend, stratification, sine wave, bimodal and shift. After diagnosing one of these common shapes from the description entered by the user, Quincy tells the user typical causes of the shape. This portion of the expert system is modular so that additional shapes and trends can be added easily. It is also intended that this shape analysis, along with the data point position analysis, could be done automatically when Quincy is interfaced with a quality control data repository.

The analysis of data point position begins with the user selecting whether the placement will be specified by halves of the chart (areas on either side of the centerline) or by σ regions A, B and C on either side of the centerline (see Figure 1). Once determined, the user is asked for number and location of points commencing with those most likely to indicate an out of control situation. Number of consecutive points falling in certain regions are analyzed via ratios and total numbers to decide if a process is out of control. The user is queried by the system until the system can diagnose whether the consecutive points indicate an out of control situation, or not.

4.3 CHOOSING AN ACCEPTANCE SAMPLING PLAN

This portion, consisting of 46 rules, focuses on the choice of an acceptance sampling plan and calculates some measurements of the plan. Acceptance sampling based upon statistical properties is intended to reduce inspection costs and improve quality, giving an accept or reject signal for a lot of items. For destructive testing it is mandatory to use a sampling plan. Acceptance sampling can be done at any point during the process; the primary variables are lot size, sample size, the acceptable producer's risk (α risk - rejecting a good lot) and the acceptable consumer's risk (β risk - accepting a bad lot).

The system can recommend a single sample plan, a double sample plan, a multiple plan, a skip lot plan, or two types of continuous sampling plans for attribute data. The selection is based upon the sizes of the sample and the lot, the acceptance number, the inspection plan, the proportion defective, whether curtailment is employed, and relative sampling costs versus false acceptance or rejection costs. The system also tests to see if a variable type sample plan would be feasible, and can recommend two kinds of variable sample plans. The final counsel is for an appropriate U.S. Military Standard governing the type of sampling plan selected. These last rules are easily modifiable to accommodate changes.

Once a plan has been recommended, a component of the acceptance sampling rule base calculates the Probability of Acceptance, the Average Outgoing Quality, the Average Outgoing Quality Limit and the Average Total Inspection for the applicable sampling plans. These numeric quantities tell the user the impact of implementing the selected sampling plan, and are based on the acceptance number, the lot and sample sizes, and whether the sample is rectifying, i.e. bad items are replaced with good.

5.0 CONCLUSIONS AND IMPLICATIONS FOR THE FUTURE

Expert systems can augment human skills for structured and semi-structured problems and are particularly effective for small, routine decisions. Tasks which are performed better if there is ample time, the best expert always did them, or where consistent decisions are desirable are prime candidates for knowledge engineering [3]. The primary economic benefit of expert systems are increased productivity by speeding professional and semiprofessional work by factors of tens to hundreds [24]. The shortened time frame for decision making, the ever expanding number of options and the decreasing experience of decision makers are added stimuli for expert systems.

Quality control is a popular focus of new methodologies and implementations as manufacturers and service industries seek to improve their competitive edge. Although statistical quality control is already largely automated for the gathering and processing of data, improperly implemented quality control can yield erroneous and costly results, which may go unnoticed indefinitely. The problem domain, combining diagnoses and decisions based on analytical data, on heuristics and on user choice, is suited for rule based expert systems.

Quincy is a prototype system which can act either as an intelligent integrator for statistical based quality control software packages or a stand alone system. It directs the user towards appropriate solutions, analyzes quality data and advises on courses of action. The integration function makes a system like Quincy useful for both experienced and novice quality control engineers. The widespread use of quality control and its similarity from application to application further increase the value of an expert system; it can be expanded or altered to adjust to different industrial situations while retaining fundamental expertise.

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Figure 1. Sample Control Chart

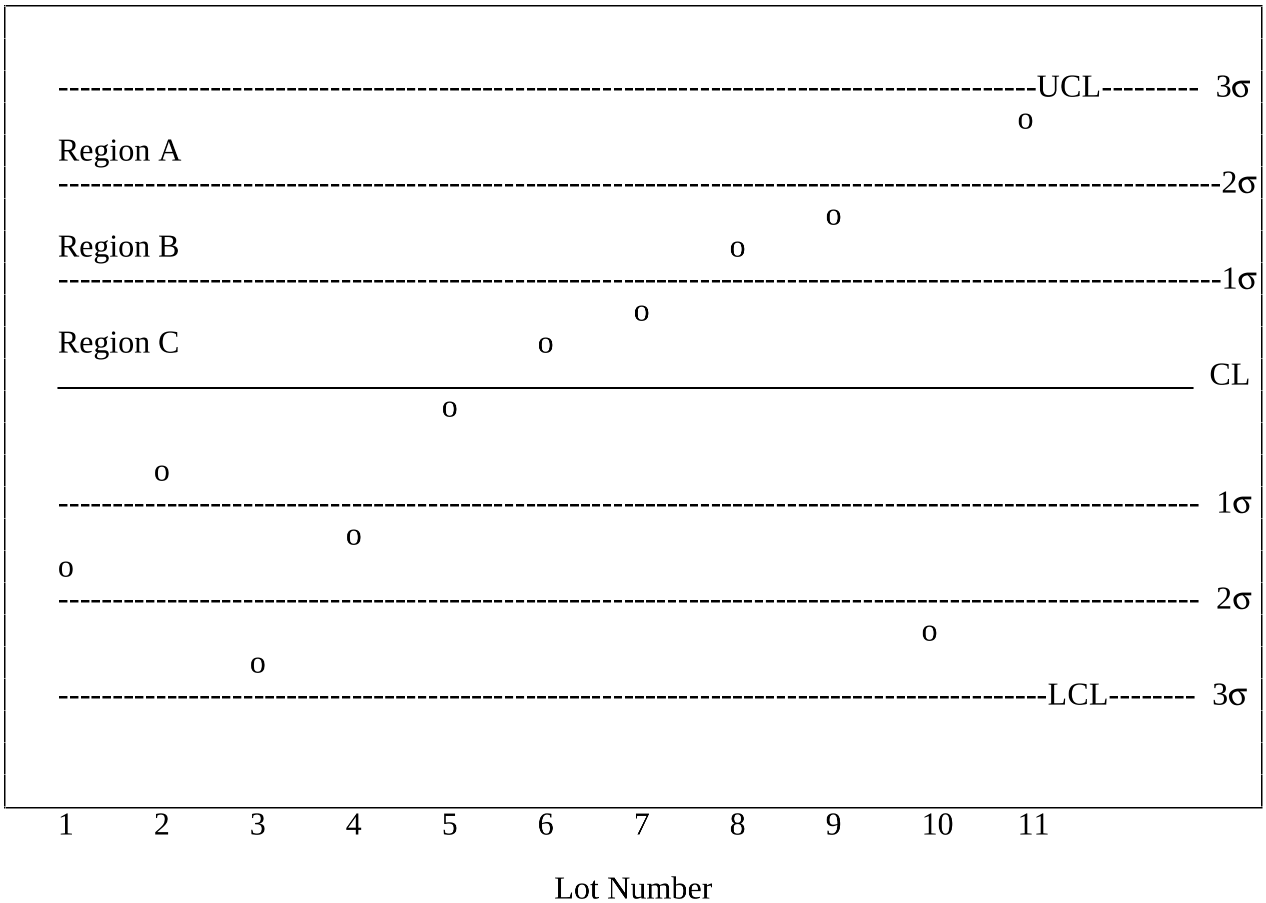

Figure 2. System Architecture of Quincy